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ABSTRACT

Commonality analysis was used to look for school effects in gains in reading test scores for 877 fourth to sixth grade children in Elementary Secondary Education Act Title I remedial reading programs. The four groups of predictor variables that were investigated were background, mental ability, parental involvement, and school program. Commonality analysis uses multiple regression procedures to partition the variance among the four groups. The criterion scores were vocabulary and comprehension scores from the Gates-MacGinitie Reading Test post-tests. Pre-test scores were included in the mental ability group of predictors. The results indicate the proportion of explained variance unique to each set of predictor variables plus the proportion common to the eleven combinations of sets. The interpretation and the advantages of commonality analysis, as well as the interpretation of negative commonalities were discussed. The technique of commonality analysis was judged to have several advantages over more traditional types of analysis. (Author/CTM)

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COMMONALITY ANALYSIS: A PRACTICAL EXAMPLE

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INTRODUCTION

This research attempts to study "school effects" by investigating the unique and common contributions of background, mental ability, program and parental involvement variables to the reading vocabulary and comprenension of students participating in compensatory education, Title I, ESEA, reading programs in Rhode Island. Commonality analysis was used as the major analytic procedure. The major objective of this paper is to outline, using the study as a practical example, the procedures utilized and interpretations made using partitioning of variance technique. In addition, methods of interpreting negative contributions of shared variance will be delineated.

BACKGROUND

Large-scale national evaluations of Title I programs (Glass, 1970; Piccariello, 1967; Gordon and Kourtrelakos, 1971; General Electric TEMPO evaluation, 1968) have produced non-significant results and concluded that the effectiveness of this compensatory education has been minimal. In addition, other recent studies (Coleman et al, 1966; Jencks et al, 1972, Cicirelli, 1969) have reported that the effect of schooling in general is low in comparison to other relevant background variables. Coleman's national appraisal of equality of educational opportunity (1966) found that what is fed into schools in the way of teachers, books, building and other resources has much less effect on achievement than the students' family background and the social environment of the student. In other words, he concluded that schools bring little influence to bear

on a child's achievement that is independent of his background and general social context. Further, a study headed by Christopher Jencks (1972) on inequality concluded that neither family background, cognitive skill, educational attainment nor occupational status explained much of the variance in income of adult men. He also concluded that school reform is not likely to have any significant effect on the degree of inequality among adults. In addition, Westinghouse/Ohio study of Head Start programs conducted by Cicirelli et al (1969) concluded that by grade two no significant differences were found in readiness scores between those who were Head Start participants and those who were non-participants.

School effects in general, and effects of Title I of ESEA in particular, would seem to be negligible when taken in the context of large macro view studies. Large scale investigations, however, have been criticized by many (Rotberg and Wolf, 1974; Averch et al, 1972; HEW Report, 1972; Lobosco, 1974) as less sensitive and exact than would be necessary to show effects of schooling on students. As the scope narrows from the nation to the states, more positive results have emerged. State evaluation reports in California (1972), Colorado (1971), Connecticut (1972) and Rhode Island (1970, 1973) indicated strong positive findings. In fact, Webb (1972) stated that it appears that more positive impact on participating children can be identified as the unit of analysis is narrowed from the nation to states to local projects.

While the evaluations of successful local projects suffered from shortcomings in generalizability to a broader population, state and national evaluations of Title I effectiveness have suffered from methodological and statistical shortcomings. In addition, the large scale evalu-

ations often failed to take into account a number of background and program variables such as intelligence, community, type of program, instructional time and student-teacher interaction that could make a difference in effective Title I reading programs.

This research was designed to overcome many of the problems that plagued earlier studies of Title I effectiveness. This investigation provides complete and relatively uniform data and a degree of representativeness hard to achieve in most other settings. For instance, a single standardized test was used, information was available on selected program, background, mental ability and parental involvement variables, equal interval unit measures were used, and pre-test and post-test information was matched for each child. This investigation has proved to be both relatively free of data problems and representative of the state of Rhode Island.

METHOD

Source of Data

The sample used in this study included 877 students in grades 4-6 enrolled in Title I remedial or corrective reading programs in the state of Rhode Island in FY 1973-74 and for whom there were appropriate grade level pre-test and post-test Gates-MacGinitie Reading Tests vocabulary and comprehension scores. In Rhode Island there has been an option to administer grade level or instructional level testing (e.g., a fifth grade participant receiving the second grade test). Only those students tested at grade level were included in this study. A review by the writer indicated that the choice to use grade or instructional testing seemed

random and there appeared to be no differential selection. For example, of those communities that are large urban areas approximately half chose to test at grade level. Similarly in those areas that can be classified as suburban and rural communities, about half chose to test at grade level and the others chose instructional level. There seemed to be no regional or size biases in the selection of testing formats.

Since those valid records utilized represented all of the usable data for Rhode Island Title I reading programs for grades 4-6, the findings of this study are statistically generalizable to the entire state where grade level testing was employed.

Data Collection

Data used in this study were collected as part of the usual Rhode Island Department of Education's Office of Compensatory Programs. Throughout the program year information was collected via four state reporting forms and the return rate was near 100 percent.

Variables Included in the Study

The following variable sets were identified:

Set 1: Background Variables

1) Type of community
2) Sex
3) Ethnic Group
4) Prior years in Title I reading programs
5) Type of school attended
6) Number of times retained in a grade

Set 2: Mental Ability Variables

1) IQ
2) Pre-test reading scores

Set 3: Program Variables

1) Pupil-teacher ratio
2) Per-pupil expenditure
3) Length of project
4) Number of days student was absent
5) Minimum amount of individual instruction per student per week
6) Size of instructional group for students
7) Number of children serviced per week
8) Amount of scheduled preparation time per week with regular teacher to discuss students
9) Whether materials were available at each child's instructional level
10) Whether materials were available on time for project start
11) Whether teachers selected materials
12) Amount of time spent by teachers per week developing their own materials
13) Whether pre-service or in-service training activities were held for staff

Set 4: Parental Involvement Variables

1) How often parents were responsible for working with students at home
2) Whether each parent was seen at least once during project year
3) Whether Parents Advisory Committee made recommendations on expenditures of Title I funds
4) Whether Parents Advisory Committee participated in the development of Title I applications
5) Whether Parents Advisory Committee reviewed Title I applications
6) Whether Parents Advisory Committee made recommendations on improvement of Title I programs
7) Whether Parents Advisory Committee participated in Title I program evaluation

Treatment of the Data

The partitioning of variance technique in multiple regression was used to analyze the data. Tatsuoka, (1969) (1971), stated that the major task in multiple regression is to construct a linear function,

$$Y' = a + b_1X_1 + b_2X_2 \ldots$$

so that the sum of the squared deviations $(y' = y)\Sigma$ between the predicted and actual Y scores on the criterion variables is as small as possible.

The efficiency of the multiple regression equation to predict the criterion variable may be determined by computing the multiple correlation coefficient (i.e., the correlation between the predicted and actual criterion scores). Classically, prediction studies have utilized quantitative, interval variables as predictors while artificially categorized variables have been used in analysis of variance and analysis of covariance.

However, Cohen, (1968) addressed the issue that though analysis of variance and analysis of covariance have traditionally been used in studies of experimentally induced variation and multiple regression analysis has been used in studies of natural variation, the systems, in the most meaningful sense, are the same. He stressed the flexibility of multiple regression techniques in handling both quantitative and qualitative predictor variables.

Mood (1971) mentioned that in education it is very difficult to create quantitative models of learning with our present limited knowledge of such structures and the specific factors related to them. To treat educational model building more appropriately he suggested the partitioning of variance technique in multiple regression for sets of variables. Mood gives the following example to illustrate the method:

> "Let us suppose that the first m of the x's are intended to be indicators of X_1 and refer to them as the W set of x's; let us lump all the other n-m's into another set and refer to it simply as the Y set. We are going to partition the variance attributable to the regression of A on the x's into three parts - rather we shall use the multiple correlation instead of the variance. We first calculate three regressions:
>
> A on the W set of x's only
> A on the Y set of x's only
> A on the whole set of x's

and let us suppose that the first removes 20 percent and the raw variance of A, the second removes 55 percent, and the third removes 60 percent. Now we divide the 60 percent removed by the whole Set (W + Y) into three parts:

a part uniquely associated with W, 5%
a part uniquely associated with Y, 40%
a part that may be associated with either W or Y 15%

The part uniquely associated with the W set is calculated by subtracting the proportion removed by the Total (W + Y) Set. The reason for attributing this 5 percent uniquely to W is simply that the x's in the Y set removed 55 percent of the 60 percent removed by the total; on adding the W set to the Y set we remove only an extra 5 percent so that it is the part that must be uniquely associated with W. Similarly, the W set alone removes 20 percent; on adding the Y set to it we remove only an additional 40 percent so that it is the part that must be uniquely associated with Y.

TABLE 1

	W	Y
Unique to W	5%	
Unique to Y		40%
Common to W and Y	15%	15%
Total	20%	55%

Finally, the part that may be associated with either W or Y is calculated by subtracting the two unique parts from the whole (60% - 5% - 40%) (Mood, 1971, p. 194-195)."

The partitioning of variance technique, as mentioned above, allows the researcher to determine both unique and common contributions of the sets to the variance of the criterion variable. This method offers advantages over more traditional types of analyses like analysis of covariance

and step-wise multiple regression. Elashoff (1969) stated that analysis of covariance should be considered when the investigator believes that some outside variable will have a large, distorting effect on the results and when the assumptions of normality of data and random assignment of subjects to treatments are met. She stated that ANCOVA is widely used to "adjust" criterion scores such as achievement for the effects of a covariate such as ability in order to compare several treatments.

The use of step-wise multiple regression allows for the identification of unique contributions of the variables to the variance of the dependent variables by determining the increase in explained variance by adding each variable to the regression equation. It is impossible, however, to determine the joint or common contributions of the sets or variables through the use of step-wise multiple regression procedures.

Since partitioning of variance is mainly a correlational technique that can look at joint contributions as well as unique elements, it seems more appropriate to use for educational model building than methods that statistically control for certain variables or does not allow for determination of common contributions.

Other problems have occurred due to the types of scores generated as dependent measures. Compensatory education studies at the local, state and federal levels have typically used gain scores on standardized reading tests to evaluate the effectiveness of programs. Gain or change scores are typically obtained by taking the difference between pre-test and post-test scores for each individual. Several authors (Bereiter, 1967, McNemar, 1969) have indicated that serious problems could result from use of this type of score. The major problem is that difference scores tend to be noticeably

less reliable than either of the two obtained scores from which they were derived. This occurs because the errors of measurement in both the pre-test and post-test score are present in the gain score. Wrightstone et al (n.d.) cited a clear example of the problem. Assume that a reading program is being evaluated. One form of a standardized reading test was used for a pre-test and another form of that same instrument was used as a post-test. If the reliability of the pre-test is .90, the reliability of the post-test is also .90 and the correlation between pre-test and post-test scores is .75, the reliability of the difference scores for the individuals in the reading program would be .60. Even though the two tests used possessed respectable reliability coefficients, the resulting gain scores proved somewhat less reliable.

A further problem in using gain scores to measure the effectiveness of compensatory education programs is a phenomenon called regression toward the mean. Regression toward the mean can occur if students are selected by virtue of being extreme on a test score and that test score is also used as the pre-test. The extent of the regression depends on such factors as the reliability of the test, or errors of measurement in the particular test used, as well as on how extreme the scores of the selected group were on the test. When a selected extreme group is identified and those scores are used as the pre-test scores, any resulting gain scores (post-test score minus pre-test score) will include both the real gain achieved by students as a result of the program as well as whatever regression effect has taken place.

To eliminate many of the common problems in dependent variables typically encountered in compensatory education evaluations, the appro-

priate standard scores (M = 50, S = 10) listed in the Gates-MacGinitie Reading Tests norming tables for vocabulary and comprehension were used as criterion variables.

Newton and Spurrell (1967) have described the statistical basis for partitioning of variance (also called element analysis or commonality analysis) and have given examples and rules for choosing primary and secondary elements in the regression. While they used single variables as predictors, Mood suggested (1971) sets of variables could also be used. The primary elements correspond to unique parts while secondary elements refer to common and total parts in Table 1 above. Newton and Spurrell (1968) have described several examples of the partitioning technique in industrial settings and have demonstrated "the power of element-analysis to uncover important features of the problem which were not apparent from the analysis by the more conventional routines. (Newton and Spurrell, 1968, p. 171)."

Three areas of concern should be noted in relation to commonality analysis. The first deals with the difficulties encountered in testing for significance. Mood (1971) stated that one could make the usual F test of significance for unique parts to determine whether additional regression terms have contributed significantly to the regression. One cannot, however, test the common parts for significance. This concern is not a major one here since this large sample study is more interested in unique and common contributions of the factors to the dependent variables than in statistical significance.

A second concern deals with the interaction of sets of variables. Tatsuoka (1973) stated that the relationships between the joint contributions of sets of variables should not be confused with the interaction

of these sets. However, if one were interested in the interaction, the product term method could be used. Kerlinger and Pedhazur (1973) cited an example in the two variable case. Assuming one had two variables, X_1 and X_2, the values of these two independent variables could be multiplied over all cases to create a third variable, X_1X_2. This variable is then entered into the regression equation as another variable, and, if there is a significant interaction between the variables in their effect on the dependent variable, it will be evident in the significance test. The analysis used in this study, however, was designed to investigate the unique and common contributions of the sets of variables on the dependent variable and not the interaction of these factors.

A third concern is that some of the commonalities can have negative signs. Kerlinger and Pedhazur (1973) stated that negative commonalities can be obtained in situations where one of the variables is a suppressor, or when correlations among independent variables are negative. Where results of this study indicated negative commonalities, an attempt was made to explain the cause.

Measures in the "school effects" realm are often rather crude and it seems doubtful that the indicators would be specific enough to provide very meaningful data by themselves. Partitioning of variance technique is especially appropriate to analyze data of this type since it assumes that the proportion of variance associated with a factor would have more stability than would regression coefficients for the specific variables within those factors. Mood offers a concluding rationale for using partitioning of variance for factors rather than multiple regression on individual indicators of that factor by stating the following:

1) "Models involving a great many variables might be more easily comprehended and better related to the work of others if the variables are combined into relatively few fundamental factors. In the present state of our understanding of education, the factors would have to be selected mostly by intuition.

2) Partitioning of regression variance appears to be a useful tool for attempting to develop relatively independent factors and to seek out reasonably specific indicators for them.

3) One line of early development of learning models might confine itself to two or three broad factors. When their structure is well understood, the next stage of development might attempt to break one or more of those broad factors down into two or three less comprehensive factors and use them to create more elaborate structures. (Mood, 1971, pp. 200-201)."

RESULTS

The data were analyzed by using the partitioning of variance technique in multiple regression to determine the unique and joint contributions of four sets of variables in the reading achievement of compensatory education students in Rhode Island. A computer program written by Polit and Rakow (1974) at Boston College designed to perform commonality analysis was utilized. Separate analyses were conducted for vocabulary and comprehension scores.

Four sets of variables were included in the analyses. The background set included six variables. Two variables in the set - type of community and ethnic group - necessitated the construction of dummy variable coding for these indicators. The mental ability set included two variables. The reading program set included thirteen variables re-

lated to instructional and program elements. The parental involvement set included six variables in the analysis. Seven variables were initially intended to be used; however, preliminary analyses indicated a high relationship between two - participation of Parents Advisory Committee in the development of Title I applications and review of Title I applications by Parents Advisory Committee - about +.80, so an additional variable combining these two was constructed.

Vocabulary Analysis

The first analysis was performed using the four sets specified above with post-test vocabulary standard scores as the dependent variable. The total amount of explained variance accounted for by the four sets of variables was sixty percent.

Background Set -

The unique contribution of the set of six background variables to the variance of vocabulary scores was about seven percent. In addition, the overlap variance, i.e., that variance shared jointly with other sets was about ten percent.

Mental Ability Set -

The unique contribution of the set of two mental ability variables to the variance of vocabulary scores was about thirteen percent. The overlap variance associated with this set was about nine percent.

Program Set -

The unique contribution of the set of thirteen program-related variables to the variance of vocabulary scores was about nine percent. In addition, the overlap variance for this set equaled about five percent.

Parental Involvement Set -

The unique contribution of the set of six parental involvement variables to the variance in vocabulary scores was about nine percent. Also, the overlap variance associated with this set was seven percent.

Only unique and overlap contributions have been mentioned here; however, the complete set of commonality coefficients are presented in Table 1.

Comprehension Analysis

The second analysis was performed using the four sets of variables specified and post-test comprehension standard scores as the dependent variable. The total amount of explained variance accounted for by the four sets of variables was about forty-six percent.

Background Set -

The unique contribution of the set of six background variables to the variance of comprehension scores was about seven percent, while the overlap variance associated with the background set was about four percent.

Mental Ability Set -

The unique contribution of the set of two mental ability variables to the variance in comprehension scores was about twenty-five percent while overlap variance was about four percent.

Program Set -

The unique contribution of the set of thirteen program-related variables to the variance in comprehension scores was about five percent, while the overlap variance was slight, about .4 percent.

TABLE 1

PROPORTIONS OF EXPLAINED VARIANCE OF FOUR SETS

OF VARIABLES ON READING VOCABULARY

AFTER PARTITIONING

	Sets of Variables			
	1	2	3	4
Unique to Set 1, (Background)	.0689			
Unique to Set 2, (Mental Ability)		.1313		
Unique to Set 3, (Program)			.0867	
Unique to Set 4, (Parental Involvement)				.0943
Common to Sets 1 and 2	.0398	.0398		
Common to Sets 1 and 3	.0842		.0842	
Common to Sets 2 and 3		.0228	.0228	
Common to Sets 1 and 4	.0580			.0580
Common to Sets 2 and 4		.0563		.0563
Common to Sets 3 and 4			.0900	.0900
Common to Sets 1, 2, and 3	.0031	.0031	.0031	
Common to Sets 1, 3, and 4	-.1003		-.1003	-.1003
Common to Sets 2, 3, and 4		-.0466	-.0466	-.0466
Common to Sets 1, 2, and 4	.0150	.0150		.0150
Common to Sets 1, 2, 3, and 4	-.0036	-.0036	-.0036	-.0036
	.1651	.2182	.1362	.1631

Parental Involvement Set -

The unique contribution of the set of six background variables to the variance in comprehension scores was about four percent. The overlap variance was about three percent.

While unique and overlap contributions have been presented here, the complete set of commonality coefficients for the comprehension analysis are shown in Table 2.

DISCUSSION

Before delving into the results of the study, it is important to first mention the methodology used for analysis in this and other similar studies. While many types of analysis are possible, the researchers doing input-output type studies have overwhelmingly chosen regression analysis as the primary analytic method. Beaton (1973) states, however, that regression analysis model seems most useful when the independent variables are truly independent in the sense that they can be manipulated to a large degree by the experimenter. For field studies done in a real-life, educational setting, it is extremely unlikely that, given the present state of our knowledge about exactly what "works" in education, sets of predictors can be identified that are correlated with the criterion variable yet independent of each other.

While partitioning of variance technique (also called commonality analysis) does not alleviate the problem of correlations among predictor variables, it does offer a decided advantage in specificity. Partitioning of variance technique is an attempt to explain the relative predictive

TABLE 2

PROPORTIONS OF EXPLAINED VARIANCE OF FOUR SETS OF VARIABLES ON READING COMPREHENSION AFTER PARTITIONING

	Sets of Variables			
	1	2	3	4
Unique to Set 1, (Background)	.0682			
Unique to Set 2, (Mental Ability)		.2511		
Unique to Set 3, (Program)			.0547	
Unique to Set 4, (Parental Involvement)				.0436
Common to Sets 1 and 2	.0147	.0147		
Common to Sets 1 and 3	-.0073		-.0073	
Common to Sets 2 and 3		.0042	.0042	
Common to Sets 1 and 4	-.0081			-.0081
Common to Sets 2 and 4		.0242		.0242
Common to Sets 3 and 4			-.0062	-.0062
Common to Sets 1, 2 and 3	-.0059	-.0059	-.0059	
Common to Sets 1, 3 and 4	.0156		.0156	.0156
Common to Sets 2, 3 and 4		-.0254	-.0254	-.0254
Common to Sets 1, 2 and 4	.0020	.0020		.0020
Common to Sets 1, 2, 3 and 4	.0289	.0289	.0289	.0289
	.1081	.2944	.0586	.0752

power of all predictor variables, both uniquely and in combination with other variables. It is a method of analyzing the variance of a dependent variable into common and unique variances to help identify the relative influences of independent variables. The method is based on the premise that the variance of the criterion variable which is predicted from a set of correlated variables may be partitioned into the independent (unique) and combination (joint) contributions of those variables to the prediction. Beaton (1973) stated the same idea in statistical terms, "The squared multiple correlation is broken up into elements assigned to each individual regressor and to each possible combination of regressors. The elements have the property that the appropriate sums not only add to squared multiple correlations with all regressors, but also to the squared multiple correlation of any subset of variables, including the simple correlations. (Beaton, 1973, p. 2)." Veldman (1975) stated that by identifying the proportion of criterion variance associated with every unique and joint source, all effects are made explicit in an unambiguous manner. The unique contribution of variables can be thought of as the proportion of variance attributed to a particular variable or set of variables, above and beyond the variance accounted for by the other independent variables or sets in the regression equation. Joint contributions of variables can be thought of as the degree the overlap of correlated variables or sets are predictive of the criterion. The size of the overlap reflects the degree of correlation.

Vocabulary Analysis - Unique Contributions

The results indicated that the background set uniquely accounted for less of the variance (about seven percent) in the criterion,

vocabulary achievement standard scores, than any of the other three sets. Mental ability, program and parental involvement sets accounted uniquely for thirteen, nine, and nine percent respectively. It is interesting to note that the background set accounted totally for nearly seventeen percent of the variance, but only seven percent could be uniquely attributed. Thus the degree of overlap for the background set is relatively large.

Averch et al (1972) stated that in studies of the input-output variety, like this one, background factors are always important determiners of educational outcomes. Why then does background uniquely account for so little of the variance in this study? Several possible explanations seem plausible. For instance, most of the studies done previously have not used commonality analysis and hence have not looked at the "unique" contribution of background variables. This study found a fairly large percent of the variance accounted for by background, however, a relatively small percent of variance was found to be uniquely attributable to the background set. Another plausible explanation could be that the variables included in the background set might not have been complete enough. Since the study used data that had already been collected, it was impossible to gather information on other relevant background variables such as parents' educational status, occupations or income level.

While this information would certainly have added to the completeness of the variable set, the differences produced by adding such variables should be less in an investigation dealing with compensatory education students rather than in a study involving general population subjects.

Title I participants must, by law, reside in areas of their community designated as low income target-areas. The relatively low unique values for background were much less than those anticipated by this researcher.

The variance uniquely attributable to the instructional program set and the parental involvement set were rather high. Some authors, Averch et al (1972) and Summers and Wolfe (1974), have stated that numerous studies have indicated that school resources do not appear to exert a strong influence on student educational outcomes. The Summers and Wolfe study (1974) does offer some hope by isolating class size, school size, teacher experience, and ratings of colleges attended as variables that appear to make a difference in student outcomes. Physical characteristics of schools as well as characteristics of personnel further removed from the students, like principals, do not appear to be powerful determiners. Few studies have examined finer distinctions like the actual program and parent involvement variables utilized in this investigation. Since both the program and parental involvement variables show relatively high contributions and are directly related to programmatic details, it may well be that as researchers begin to identify inputs that more directly impinge upon students like instructional grouping, instructional materials and parental help at home that school effects will become more evident. As more appropriate analyses are tried, it may be that more subtle differences can be delineated.

Vocabulary Analysis - Joint Contributions

Since the partitioning of variance technique is a relatively new and developing methodology, there is no clearcut scheme to utilize in

interpreting the joint contributions. Kerlinger and Pedhazur (1973) stated that the object of the commonality analysis is to obtain large unique values and small joint contributions. With the exception of the background set, the other three sets resulted in higher unique values than total overlap value. It is important to note that negative commonalities occurred among some of the hoint contributions in this analysis. The problem of negative commonalities and possible explanations for their existence are presented later in this section.

Comprehension Analysis - Unique Contributions

As in the first analysis, this analysis using comprehension subtest standard scores as the dependent variable, the background set seemed to be less influential than originally expected, accounting for about seven percent of the variance in comprehension scores. Plausible explanations such as lack of additional pertinent background information or the use of the more detailed analysis may be affecting the results.

Relatively similar unique contributions were found for the program and parental involvement sets, five, and four respectively. While these values are smaller than those found in the first analysis, they are fairly close to the background set and, therefore, are taken into consideration here.

The largest value, by far, however, was for the mental ability set. Twenty-five percent of the variance was uniquely accounted for by this set. The findings could be important when the type of method used by the test to measure reading comprehension is considered. Traditionally, the post-question technique has been used to measure reading comprehension. The post-question technique emphasizes the mental

function of memory as the prime factor in comprehension. This may account for the relatively high correlations conventionally found between intelligence and reading comprehension ability. The Gates-MacGinitie Reading Tests, however, uses a modified cloze technique which is designed to measure more language understanding than memory function. This research may provide some data about the relationship between intelligence and comprehension as measured by cloze techniques.

Comprehension Analysis - Joint Contributions

The commonalities or joint contributions of the sets were extremely small in relation to the unique values. As a result, the overlap variance for each set is relatively small.

Negative Commonalities

When partitioning of variance technique is used, there exists the possibility of obtaining negative commonalities, that is, to obtain negative proportions of shared variance. Beaton (1974) stated that the unique elements must be non-negative but the common parts may be either positive, negative or zero. He also mentioned that negative commonalities are not usually found in educational research. This statement may be a bit premature since partitioning of variance technique has been used in relatively few educational studies and has only recently been identified as a promising method in educational research.

The results of this study indicated some negative commonalities, most notably a -.1003 value for the joint contributions of the background, program and parental involvement sets in the vocabulary analysis. The interpretation of negative commonalities is not clear since the methodology is still in the developing stages.

Negative commonalities are clearly possible in partitioning of variance. A hypothetical example should make this evident. Assume the two variable case, where Variable A and Variable B are used to predict the criterion Variable C, with the following squared multiple correlations: $R^2_{AC} = .50$, $R^2_{BC} = .00$, $R^2_{AB} = .40$, and $R^2_{ABC} = .60$. To determine the unique contribution of variable A, the following formula could be used:

$$U_A = - R^2_{BC} + R^2_{ABC} = - .00 + .60 = .60.$$

To determine the unique contributions of variable B, the following formula could be used:

$$U_B = - R^2_{AC} + R^2_{ABC} = - .50 + .60 = .10.$$

The common contribution of variables A and B could be determined by the following formula:

$$C_{AB} = R^2_{ABC} - U_A - U_B = .60 - .60 - .10 = -.10.$$

The -.10 value for C_{AB} represents a negative proportion of shared variance.

Several authors (Newman and Newman, 1975, Kerlinger and Pedhazur, 1973) acknowledge this as a conceptual problem yet offer little direction or explanation to solve the difficulty. Other writers supply more direction and information.

Veldman (1975a) suggested that in a situation like the one presented above a negative commonality results from a suppressor variable. A suppressor variable is related to another predictor variable yet unrelated to the criterion. In this way the variable suppresses the variance in another predictor which is unrelated to the criterion. The prediction

of the criterion is increased by the inclusion of a suppressor variable into the regression equation.

The correlation matrix of variables was examined for indications of suppressor variables. Several instances of this type of relationship were found.

Beaton (1973) and Veldman (1975b) have also suggested that negative commonalities can occur when correlations between independent variables or sets of variables are negative. In this situation one variable or set actually confounds the predictive power. Beaton (1973) gives an example of a relationship of this type:

> "Both weight and speed are important to success as a professional football player and each would be moderately correlated with a measure of success in football. Weight and speed are presumable negatively correlated and would have a negative commonality in predicting success in football. If both weight and speed are known, one would expect to make a much better prediction of success using both variables to select fast, heavy men rather than just selecting the fastest regardless of weight or heaviest regardless of speed. Thus the negative commonality indicates that explanatory power of either is greater when the other is used (Beaton, 1973, p. 22)."

In order to shed some light on possible negative correlation between variables within sets, the correlation matrix was again examined. Examples of this type of relationship were found to exist.

For purposes of interpreting the negative commonalities found in this study several statements and cautions should be made.

1) The coefficients presented in Tables 1 and 2 are shown to the precision of four decimal points. This was done to indicate complete results and in the event that this type of precision would be useful to readers of this study; however, it is certainly defensible to round off several of the coefficients.

2) If this is done, many of the negative commonalities presented in the tables become essentially zero. After rounding, no negative commonalities appear for any second order combination, only in the third order joint contributions.

3) Given the nature of the variable sets as well as some indications from the correlation matrix that negative correlations between some variables exist, it is the opinion of this writer that the negative commonalities are more likely to be due to negative correlations between sets than in suppressors. In many cases variables in each set of predictors were related positively to the dependent variables but negative correlations between variables in different sets existed.

4) When interpreting tables, Veldman (1975b) suggested that when negative commonalities are obtained, the independent contributions of the sets or variables involved are collectively overestimated.

5) Perhaps as educational models become better defined, the occurrence of negative commonalities will diminish. However, as commonality analysis is increasingly utilized, further research and guidelines on interpretation of these scores should be developed.

In conclusion, this investigation utilized a newly developed methodology, commonality analysis, in a school effects study. The technique provided several advantages over more traditional types of analysis and proved highly satisfactory in the study. It is hoped that this method will be increasingly used in future educational research investigations.

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